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A COMPREHENSIVE SURVEY OF NEXT-GENERATION OPTIMIZATION ALGORITHMS FOR TARGET COVERAGE IN MOBILE WIRELESS SENSOR NETWORKS*

MOBİL KABLOSUZ SENSÖR AĞLARINDA HEDEF KAPSAMA İÇİN YENİ NESİL OPTİMİZASYON ALGORİTMALARINA YÖNELİK KAPSAMLI BİR DERLEME

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Abstract

In recent years, Wireless Sensor Networks (WSNs) have gained attention due to their real-time monitoring capabilities. These networks use low-power devices to collect and transmit data, becoming significant with the rise of 5G and the Internet of Things (IoT). Initially used for military purposes, WSNs have expanded into various sectors, particularly in smart agriculture, where they enhance efficiency through modern technology. By providing real-time data, WSNs help farmers optimize yields, reduce waste, and improve productivity, supporting the digital transformation of agriculture. Despite their advantages, WSNs face challenges such as routing, localization, energy efficiency, and coverage. This study provides a comprehensive survey of the coverage optimization problem in WSNs, focusing on meta-heuristic algorithms such as the Gray Wolf, Whale Swarm, Flower Pollination, and Cuckoo Algorithms. These algorithms are analyzed based on metrics like maximum coverage rate, energy consumption, and solution time. The survey highlights their potential to address challenges in WSN applications, particularly in agriculture and other domains, by optimizing sensor placement and improving network efficiency.

Keywords: Target coverage optimization, wireless sensor networks, meta-heuristic optimization algorithms.

Öz

Son yıllarda Kablosuz Sensör Ağları (WSN), gerçek zamanlı izleme yetenekleri sayesinde dikkat çekmektedir. Bu ağlar, düşük güçlü cihazlar kullanarak veri toplar ve iletir, 5G ve Nesnelerin İnterneti (IoT) ile birlikte daha da önemli hale gelmiştir. İlk olarak askeri amaçlarla kullanılan WSN'ler, günümüzde özellikle akıllı tarımda modern teknolojilerle verimliliği artırmak için yaygın bir şekilde kullanılmaktadır. Gerçek zamanlı veriler sağlayarak çiftçilerin verimliliği optimize etmesine, atıkları azaltmasına ve üretkenliği artırmasına yardımcı olmakta ve tarımın dijital dönüşümünü desteklemektedir. Avantajlarına rağmen, WSN'ler yönlendirme, konumlandırma, enerji verimliliği ve kapsama gibi zorluklarla karşılaşmaktadır. Bu çalışma, WSN'lerdeki kapsama optimizasyon problemini ele alan kapsamlı bir derleme sunmaktadır. Gri Kurt, Balina Sürüsü, Çiçek Tozlaşma ve Guguk Kuşu Algoritmaları gibi meta-sezgisel algoritmalar, maksimum kapsama oranı, enerji tüketimi ve çözüm süresi gibi metrikler temelinde analiz edilmiştir. Çalışma, bu algoritmaların özellikle tarım ve diğer alanlardaki uygulamalarda karşılaşılan zorlukları ele almadaki potansiyelini, sensör yerleşimini optimize ederek ve ağ verimliliğini artırarak vurgulamaktadır.

Anahtar Kelimeler: Hedef kapsama optimizasyon, kablosuz algılayıcı ağlar, meta-sezgisel optimizasyon algoritmaları.

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1. INTRODUCTION

The development of 5G and Internet of Things (IoT) technologies expand the application areas of Wireless Sensor Networks (WSN), offering more effective solutions in various fields such as military, agriculture, healthcare, industrial automation, and environmental monitoring. WSNs, which have been particularly utilized in military applications, have gained broader opportunities for usage with the influence of 5G and IoT technologies (Rawat et al., 2014). In military applications, WSNs hold strategic importance, playing a vital role in areas such as security and surveillance to detect enemy activities and protect strategic regions. By providing real-time data to military units, WSNs strengthen operational decision-making processes and enhance the effectiveness of military forces.

Wireless sensor networks play a significant role in various application areas such as environmental monitoring, data collection, and transmission. These networks provide a structure where sensor nodes can interact wirelessly with each other and detect changes in the environment. They consist of systems comprising low-power consumption and small-sized sensor nodes. These sensors are electronic devices that collect environmental data, such as temperature, humidity, motion, etc., and transmit it to a central unit. However, the placement of these devices in the monitored areas is often done randomly due to cost and complexity reasons. Random placement has several disadvantages that negatively affect the effectiveness and efficiency of sensor networks (Li & Zhang, 2010). Among these disadvantages, factors such as efficiency loss and data interruption play a significant role. Additionally, challenges such as increased energy consumption, imbalance in coverage areas, and cost escalation may also be encountered. Therefore, strategically placing sensors and carefully planning coverage areas are crucial to increase efficiency and minimize disadvantages.

In mobile wireless sensor networks (MWSNs), the target coverage problem refers to the ability of sensor nodes to cover all or specific targets in a given area. With randomly placed sensors in MWSNs, the entire area where data is to be collected may not be fully covered. This results in incomplete data collection in certain regions of the monitored area, leading to inaccurate analyses and ineffective decision-making. Moreover, the imbalance in coverage areas may lead to excessive data density in certain areas and insufficient data in others, negatively impacting the performance of the sensor network. To address these issues, strategic placement and data collection methods are crucial.

The coverage problem in WSNs can generally be defined as a measure of whether a network area is effectively monitored by sensor nodes. This problem is one of the fundamental issues directly affecting the energy consumption and network lifetime of WSNs. The coverage problem aims to achieve maximum coverage with the placement of the minimum number of sensor nodes. Being NP-Hard, meaning lacking a polynomial-time algorithm that solves all instances optimally, this problem falls into a category of challenging optimization problems (Hanh et al., 2016). NP-Hard problems are known for their difficulty and complexity since there is no polynomial-time algorithm that optimally solves all instances. Typically, acceptable solutions are sought for NP-Hard problems, or constraints are introduced to make them easier.

Coverage problems in WSNs can be classified into three categories: target coverage problem, area coverage problem, and barrier coverage problem. In the target coverage problem, there are specific targets that need to be monitored by mobile sensors. Due to limited energy resources, it is important to ensure effective coverage of the monitored area. Area coverage problems aim to have at least k sensors covering each point in a specific area. Barrier coverage problems, on the other hand, target the detection of objects moving along a barrier (Ozdag & Canayaz, 2021).

Next-generation meta-heuristic algorithms can be highly effective in solving NP-Hard problems such as the target coverage problem. These algorithms typically consist of evolutionary computation, artificial bee colonies, particle swarm optimization, and similar techniques. Their characteristic feature is the ability to generate fast and optimized solutions over large datasets. The use of next-generation meta-heuristic algorithms in solving complex problems like the target coverage problem is a significant step towards enhancing the effectiveness of WSNs. These algorithms can optimize the strategic placement of sensor nodes, reduce energy consumption, and maximize the coverage area of the network. Consequently, next-generation meta-heuristic algorithms are considered as important tools in overcoming critical challenges like the target coverage problem, enabling WSNs to operate more efficiently and effectively.

The main objective of this study is to comprehensively evaluate the performance of next-generation meta-heuristic algorithms used in various fields for solving the target coverage problem in the literature. This evaluation aims to determine how different algorithms approach the target coverage problem and under what conditions they are more effective. Additionally, by identifying the limitations of existing algorithms and potential areas for improvement in the current literature, the study aims to provide guidance for future research. In this way, a new perspective is brought to research on the target coverage problem in WSNs, aiming to contribute to the more effective utilization of algorithms in practical applications. This study aims to provide guidance on algorithm selection for individuals working in this field, encouraging effective utilization of these methods. By evaluating a wide range of algorithms and facilitating appropriate selections, the research aims to enhance efficacy within the sector.

Sections 2 and 3 respectively contain a literature review and the materials and methods used in the literature search. Section 4 provides the mathematical formulation of the problem, while Section 5 discusses the advantages and disadvantages of some of the metaheuristic algorithms investigated in the study. The final section, Section 6, presents the conclusions of the study.

2. LITERATURE REVIEW

In recent years, WSN technology has made significant advancements, with application areas encompassing industries, smart agriculture, environmental conservation, healthcare, and many others (Sharma & Gupta, 2022; Qadir et al., 2020; Akyildiz et al., 2002). Today, with the development of smart agriculture applications, the use of WSNs has become widespread to better fulfill the task of acquiring information and sensing about agricultural land environments. The foundation of smart agriculture application lies in the collection and processing of soil environment information. In a study conducted by Li (Li, 2022), an algorithm was proposed to address coverage holes caused by the failure of nodes in Wireless Sensor Networks (WSNs). This algorithm, based on the behavior of artificial fish swarms, efficiently simulates node movements to repair these holes with minimal energy consumption and node displacement, thereby improving overall network coverage and extending its operational lifetime. To enhance the effectiveness of the optimization, new actions and self-adaptive vision and step length are used. The algorithm quickly repairs holes with minimal node movement, thereby increasing WSN coverage and extending the network's lifetime. Simulation results show that the algorithm provides high accuracy, efficiency, and robustness. Coverage is considered one of the most important factors contributing to the quality of WSN systems (Liang et al., 2021). Therefore, the coverage optimization problem has been extensively investigated in the literature, and numerous studies have been conducted on this topic. In the literature, there are studies focusing on improving coverage area and network lifetime by efficiently and effectively utilizing the energies of the sensors. In these studies, mathematical models of the problem have been first established, and then meta-heuristic approaches yielding optimal or near-optimal results have been developed based on these models. Figure 1 illustrates the types of algorithms used in solving Coverage Optimization problems as general categories. The algorithms used in solving coverage optimization problems can be categorized into three main headings: mathematical algorithms, heuristic algorithms, and meta-heuristic algorithms.

Mathematical algorithms typically define the problem as a mathematical model and develop a solution strategy suitable for this model. These algorithms usually leverage mathematical techniques to optimize the constraints and objective function of the problem. Mathematical algorithms may vary based on the structure and size of the problem, and they typically strive to optimize the problem effectively while efficiently utilizing computational power during the solution process.

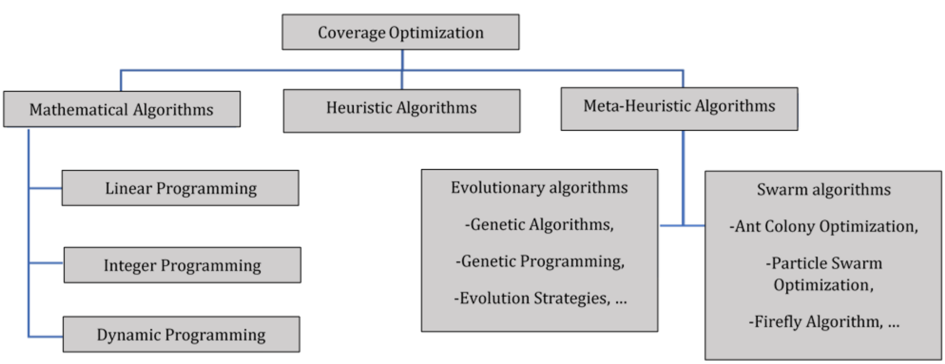

Figure 1. Types of Algorithms Used in Solving Coverage Optimization Problems

Heuristic algorithms are often methods inspired by natural systems or social behaviors to solve problems. These algorithms typically explore potential solutions in the solution space using a set of heuristic rules or metaphors. Heuristic algorithms generally require less computational power to solve the problem and can produce effective solutions in a specific problem domain.

Meta-heuristic algorithms are methods that combine multiple heuristic algorithms to provide stronger and more flexible solutions. These algorithms work on a population or solution set created by the combination of different heuristic algorithms to optimize the problem. For example, evolutionary programming, which consists of a combination of evolutionary strategies and genetic algorithms, leverages both the flexibility of genetic algorithms and the effective solution potential of evolutionary strategies in the problem domain. Thus, meta-heuristic algorithms can offer more effective and consistent solutions in complex problems like coverage optimization.

These algorithms offer different approaches to solve coverage optimization problems and can be preferred based on suitability to a specific problem domain.
In a study conducted by Jia et al. (2009), the issue of sustaining detection coverage in wireless sensor networks with low energy consumption and a reduced number of active sensor nodes was examined. In the study, a detection model addressing a large number of randomly placed and adjustable sensing radius sensors was proposed. This model was implemented with a novel coverage control scheme based on the elitist non-dominated sorting genetic algorithm (NSGA-II). Sensor selection and sensing radius adjustment were improved using binary coding methods. The results demonstrated the fast and effective nature of NSGA-II.

In a study by Wang et al. (2018), a wireless sensor network coverage optimization model based on an enhanced whale optimization algorithm (WOA) was proposed. The mathematical model of node coverage in wireless sensor networks was developed to achieve complete coverage for the area of interest. The algorithm presented in the study was developed with the idea of reverse learning to optimize the initial distribution of the population, unlike the whale swarm optimization algorithm. Experiments showed that this algorithm could effectively improve the coverage area of nodes in WSNs and optimize network performance.

Deepa and Venkataraman (2021) combined the WOA with a Levy flight mechanism (LWOA) to address the weak exploration problem in WOA. The proposed method enhances the exploration ability of WOA and improves global search capacity, convergence efficiency, and overall network performance. Compared to WOA, LWOA significantly improves network coverage.

Guo et al. (2013) proposed a multi-objective cultural algorithm inspired by quantum mechanics to solve the multi-objective optimization problem of network coverage rate and energy efficiency of wireless sensor networks. The algorithm effectively utilizes information obtained from the dominant individual set and encourages more efficient search. Simulation results indicate that the wireless sensor network arrangement obtained with this algorithm has a higher network coverage rate and a lower node redundancy rate.

Artificial bee colony algorithm was utilized to increase the network lifetime for solving energy-efficient coverage problem of sensor networks (Khalaf et al., 2020; Roselin & Latha, 2016). In a study by Zhu and Wang (2021), the hybrid strategy grasshopper algorithm (LRDE_IWO) was used to optimize the coverage rate. This algorithm prevented early convergence and accelerated convergence by balancing global and local search capabilities and optimizing the competitive process. Zang et al. (2021) claimed that the newly optimized gray wolf algorithm, simulated annealing, improved coverage area, reduced energy consumption, and extended the network lifetime of wireless sensor networks compared to other optimization algorithms such as particle swarm optimization and standard gray wolf optimization.

Chowdhury proposed a Dynamic Fuzzy Inference System Based Reverse Glowworm Swarm Optimization (FIS-RGSO) algorithm for mobile wireless sensor networks aiming to minimize energy consumption and maximize area coverage by applying limited and organized sensor movements (Chowdhury & De, 2020). In a study by Lee et al. (2017), a new Ant Colony Optimization (Three Pheromones ACO, TPACO) algorithm was proposed to solve the Efficient-Energy Coverage Problem in Wireless Sensor Networks. TPACO was shown to be more successful than classical ant colony algorithms. Arivudainambi and his colleagues (2017) proposed a deterministic distribution strategy using the cuckoo search algorithm to minimize energy consumption and maximize target coverage area in three-dimensional underwater wireless sensor networks.

In a study by Jiao et al. (2022), an improved flower pollination algorithm (IFPA) was proposed to optimize sensor nodes' coverage and connectivity problems in monitoring areas with complex terrain and harsh environments while minimizing energy consumption. Fang and Sun (2017) developed an enhanced artificial fish swarm algorithm-based optimization method for WSN coverage area with multiple optimization objectives. The method evaluated network coverage, node utilization, and average energy consumption together to eliminate the irrationality of randomly deploying sensor nodes. The algorithm exhibits good global search capabilities but consumes a high amount of time.

In Zhang Qi-wei's (2009) study, a hexagonal grid and Poisson distribution-based node deployment method was successfully applied to solve the problems of connectivity, coverage, and sensor distribution in WSNs. Through Matlab simulation, it was demonstrated that this method could provide uninterrupted network coverage in low node density scenarios while maintaining network connectivity.

Haifeng Ling et al. (2020) addressed the coverage area issues in wireless sensor networks and proposed a coverage optimization method based on the Fruit Fly Optimization Algorithm (FOA). The proposed FOA-based network model optimizes the coverage area by simulating the behavior of fruit flies, thereby enhancing energy efficiency. By balancing the movement and energy consumption of fruit flies, the algorithm extends the network's lifetime while improving coverage area. Similarly, Cheng et al. (2023) also proposed a method based on the Fruit Fly Optimization Algorithm (FOA) to solve coverage issues in wireless sensor networks. The results indicate that the proposed method increases coverage rate and enhances network performance.

An innovative solution called Improved Sparrow Search Algorithm (ISSA) was proposed in (Wang et al., 2023) to address the low coverage area problem in WSNs.

The authors improved the SSA algorithm by modifying the random population initialization to create balance and diversity. Additionally, a reverse learning strategy was applied to prevent falling into local optima. By resolving the issues in SSA, better coverage optimization was achieved.

In the study by Jinyan Liang et al. (2022), the focus was on the information monitoring area of Soil Moisture Wireless Sensor Networks (SMWSNs) used for precise farm irrigation. The researchers developed the Adaptive Cauchy Variant Butterfly Optimization Algorithm (ACBOA) to optimize the coverage area of SMWSNs and increase water use efficiency. Additionally, they designed a coverage optimization model that integrates node coverage area and network service quality. Simulation experiments demonstrated that the ACBOA optimization increased the coverage rate of SMWSNs by 9,09%, 13,78%, 2,57%, and 11,11% compared to other swarm intelligence algorithms (BOA, ABC, FOA, and PSO), respectively.

Qiang Zhao et al. (2022) proposed the combined use of PSO and chaos optimization. By using a method that encodes sensor locations, PSO optimized the sensors while the Variable Domain Chaos Optimization Algorithm (VDCOA) was used to achieve higher coverage rates. Six versions of VDCOA were investigated, including circular, logistic, Gauss, Chebyshev, sinusoidal, and cubic maps. All six versions outperformed PSO and CPSO, achieving coverage areas exceeding 90% in the first two cases.

In the study by Chowdhury and De (2021), effective deployment of sensor nodes, crucial for enhancing MWSN performance, was emphasized. A Voronoi - Glowworm Swarm Optimization - K-means algorithm (Voronoi-Firefly Swarm Optimization Algorithm) was introduced as an energy-efficient coverage optimization technique. By combining Glowworm Swarm Optimization, K-means algorithm, and Voronoi cell structure, this approach increased coverage area with minimum active node count. The proposed method also extended network lifetime by saving energy, and simulation results demonstrated coverage rates of up to 99,99%.

Kapoor and Sharma (2023) proposed a routing protocol inspired by firefly swarms to ensure the sustainability of energy-constrained wireless sensor networks. Glowworm swarm optimization aimed to improve network coverage area and connectivity for message transmission. As this algorithm converged faster compared to alternative techniques such as Particle Swarm Optimization, Firefly Algorithm, Grey Wolf Optimization, Genetic Algorithm, and Bat Algorithm, it showed effective potential in solving multi-objective optimization problems.

In the study by Biswas et al. (2018), a distributed shortest path data collection algorithm using sensor nodes was proposed to minimize energy consumption in WSNs. This algorithm aimed to increase network lifetime by providing connected target coverage in both static and mobile WSNs. The performance of the proposed algorithm was evaluated with parameters such as live node percentage, node load distribution, and network lifetime using the TOSSIM simulator in the TinyOS environment.

Keshmiri and Bakhshi (2020) addressed the connected target coverage problem in energy-constrained wireless sensor networks. They proposed a new two-stage optimization approach; in the first stage, maximum disjoint cover sets were created with integer linear programming, and in the second stage, a complex integer linear programming model was used to plan information gathering and transmission for targets. The effectiveness of the two-stage method was demonstrated through experiments conducted in various scenarios.

In the study by Pitchaimanickam and Murugaboopathi (2020), a hybrid approach combining Particle Swarm Optimization (PSO) with Firefly Algorithm was proposed to enhance the energy efficiency of wireless sensor networks (WSNs). This hybrid algorithm improved the selection of the optimal cluster head in the LEACH-C algorithm, resulting in energy savings. The performance of the proposed method was evaluated based on parameters such as live node count, energy efficiency, and utilization. The results showed that the proposed hybrid method achieved more efficient results by prolonging network lifetime compared to the Firefly Algorithm.

Da-Ren Chen et al. (2019) proposed a protocol called CEMST aiming to improve coverage and energy efficiency in wireless sensor networks. This protocol includes intra-cluster and inter-cluster methods considering sensor node density and coverage area overlap. Additionally, it generated balanced clustering structures using a self-balancing algorithm and Borůvka algorithm to enhance energy efficiency. Simulation results demonstrated that CEMST provided better coverage area and network lifetime.

In the study by Sampathkumar et al. (2020), the Glowworm Swarm Optimization approach (LBR-GSO) was proposed for energy-efficient routing and load balancing in WSNs. LBR-GSO utilized an enhanced route discovery algorithm for energy savings and employed a pheromone-based update strategy and energy-based transmission strategy. Evaluated in various application scenarios using MATLAB simulations, LBR-GSO demonstrated more effective improvements compared to other approaches such as ACO, EE-ACO, and s-Ant.

Weifeng Sun et al. (2020) reviewed representative Swarm Intelligence (SI) algorithms and summarized their applications in the Internet of Things (IoT), particularly focusing on SI-based applications in WSNs. Additionally, SI-based applications were evaluated in other IoT areas such as Unmanned Aerial Vehicle (UAV)-supported wireless networks, and future research expectations and trends were discussed.

Hui Wang et al. (2020) focused on the centrality of energy efficiency in the design of routing algorithms for wireless sensor networks. They developed a routing algorithm based on the Elite Hybrid Meta-Heuristic Optimization Algorithm to maximize the survival time of sensor networks communicating with the receiver node. By combining the global search capabilities of Particle Swarm Optimization, the differential operator of differential algorithm, and the pheromones of ant colony optimization, this new algorithm offered an innovative approach. The new algorithm was tested through comprehensive simulations and observed to increase the lifetime of wireless sensor networks by 38% compared to other routing algorithms.

The study by Singh et al. (2021) addressed the use of nature-inspired optimization algorithms to solve the sensor lifespan limitations in WSNs. Highlighting the importance of achieving optimum network coverage, the use of these algorithms in WSNs to reduce energy consumption of battery-operated sensors and increase network efficiency was examined. The paper classified optimization algorithms in the first half and summarized WSN problems, while the second half compared the performance of two nature-inspired algorithms: Enhanced Genetic Algorithm and Binary Ant Colony Algorithm (IGA-BACA) against Lion Optimization (LO). Simulation results showed that LO provided better network coverage and faster convergence rates.

Gunjan (2023) focused on research into the practical challenges of integrating nature-inspired multi-objective optimization (MOO) algorithms into WSNs. The study examined the use of MOO algorithms and evaluated their effects on various application domains. Providing a significant evaluation to guide future researchers, it presented an assessment of the integration of WSNs with MOO and the potential contributions of this integration.

The literature survey indicates that coverage optimization in wireless sensor networks (WSNs) is a significant research topic. Studies in this field emphasize the use of various next-generation metaheuristic algorithms to increase sensor node energy efficiency, extend network lifetime, and optimize data transmission. The findings obtained from a comprehensive literature review highlight the importance of new research and development efforts to improve WSN performance and enable more effective utilization in various application domains. These studies, which will guide future researchers, underscore the potential and significance of metaheuristic algorithms used in coverage optimization of WSNs.

3. SURVEY SCOPE AND METHODOLOGY

In this study, studies aiming to solve the coverage optimization problem, which aims to determine the optimal placement of sensor nodes in Wireless Sensor Networks (WSNs), were examined in Web of Science, Springer, Elsevier, Google Scholar, Semantic Scholar, Scopus and IEEE Xplore databases. In all databases, 522 publications referring to “WSN and/or coverage optimization” were detected in the period 2016-2023. The search on all databases focused on the following string: WSN AND Coverage AND Optimization AND Heuristic. 73 publications were selected after scope and content evaluation, and 45 publications were selected after suitability evaluation. The most important of the 45 studies analyzed are presented in Table 1.

Table 1. Overview of Algorithm Used in Coverage Optimization

Reference	**Type of algorithm used**	**Problem type**	**Advantages/Disadvantages**
St 1	Harmony Search Algorithm (HS)	Maximum Coverage	Adapts number and position of nodes to maximize coverage and minimize cost. Integrates adaptable length encoding in solution vectors, allowing dynamic adjustment of sensor counts. Superior performance in optimizing network coverage

			compared to genetic algorithms and random deployment.
St 2	Cuckoo Search Algorithm (CSA)	Maximum Coverage, Energy Consumption	When compared with the RA algorithm, the coverage rate is higher in the CSA.
St 3	Particle swarm optimization (PSO) and Voronoi diagram.	Maximum Coverage	The proposed algorithm provides better coverage area compared to PSO-Grid within a reasonable computation time.
St 4	Distributed Data Gathering Algorithm	Maximum Coverage, Network Lifetime	This paper primarily focuses on energy-efficient connected target coverage in Wireless Sensor Networks (WSN). On one hand, we propose a distributed data collection algorithm to provide energy-efficient shortest path routing, and on the other hand, we allow for multi-path routing to ensure the reliability of the network. The performance of the algorithm has been analyzed on both static and mobile WSNs. We observed that mobile WSNs outperformed in terms of both network lifetime and live node percentage.
St 5	Coverage- and energy-aware method with minimum spanning trees (CEMST)	Maximum Coverage, Energy Consumption, Network Lifetime	This paper proposes a coverage and energy-aware method with Minimum Spanning Trees (CEMST) for multi-hop clustered WSNs. In CEMST, the cluster size is detailed with all experiments, and the effectiveness of proposed parameters such as sensor overlap degree, node density is examined. The distance to the BS is used to balance node energy consumption using self-organizing algorithms. Compared with existing methods, CEMST forms more suitable cluster structures and energy-efficient routes.

St 6	Energy-improved Fruit Fly Optimization Algorithm (E-FOA).	Maximum Coverage, Network Lifetime	OA has been improved in terms of energy so that the algorithm can monitor the energy of each node, stop iterations when the node energy is low, reduce node energy loss, and decrease the number of dead nodes. This enhanced method optimizes the coverage area of the wireless sensor network.
St 7	Fuzzy Inference System Based Reverse Glowworm Swarm Optimization (FIS-RGSO)	Maximum Coverage, Energy Consumption	The FIS-RGSO algorithm demonstrates that it is more energy-efficient compared to the previous EEMRGSO algorithm. It reduces sensor movements to minimize the total distance covered, thus increasing the network's lifespan. Additionally, it improves the utilization of the sensor's detection area by reducing the overlap with neighboring sensors.
St 8	Energy-efficient coverage optimization based on K-means-Voronoi-GSO algorithm	Maximum Coverage, Network Lifetime	The approach proposed in this paper, developed using the GSO algorithm, K-means algorithm, and Voronoi, has shown the best performance, reaching a coverage rate of 99,99% when compared with 7 different algorithms.
St 9	Levy Flight mechanism with WOA (LWOA)	Maximum Coverage	The LWOA algorithm, by enhancing and balancing the exploration capability of WOA, can facilitate the capture of local optima. When compared with Particle Swarm Optimization and Whale Optimization Algorithm, LWOA can effectively increase the coverage area of wireless sensor network nodes, achieving a higher coverage rate with fewer nodes. As a result, the total cost of deploying the network is minimized.
St 10	Artificial Fish Swarm Algorithm (AFSA)	Maximum Coverage, Energy	The speed of escaping local optima has been improved by introducing such a fusion with virtual force. However, the algorithm still has disadvantages such as delayed

		Consumption	response to serious local optimization and noticeable improvement in coverage performance.
St 11	Multi-objective real-coded quantuminspired cultural algorithm (MORQCA)	Maximum Coverage, Energy Consumption	This algorithm demonstrates that the wireless sensor network layout obtained achieves a higher network coverage rate and a lower node redundancy rate.
St 12	Non-dominated sorting genetic algorithm (NSGA-II)	Maximum Coverage, Energy Consumption	Traditional NSGA overcomes disadvantages such as high computational complexity, premature convergence, and the necessity of assigning sharing parameters.
St 13	Improved flower pollination algorithm (Improved - FPA)	Maximum Coverage, Energy Consumption	The I-FPA algorithm demonstrates higher search efficiency and accuracy compared to standard FPA, IGWO, AIFS, and IPSO. Simulation results confirm that our proposed CCFPA can achieve 100% coverage and connectivity with fewer sensor nodes and less movement energy usage.
St 14	Improved GSO	Maximum Coverage, Energy Consumption	The proposed technique's applicability in terms of solution efficiency has been compared with alternative techniques such as Particle Swarm Optimization, Firefly Algorithm, Grey Wolf Optimizer, Genetic Algorithm, and Bat Algorithm. Findings indicate that our technique outperforms the others due to the high likelihood of providing globally optimized solutions for multi-objective optimization problems, especially in terms of convergence speed.
St 15	New 2-phase optimization method	Maximum Coverage, Energy Consumption	The proposed two-phase system improves the lifespan compared to OECCH and EECC due to the creation of more qualified cluster heads (CS).
St 16	Bee algorithm	Maximum Coverage	According to the results obtained, the bee algorithm provides a better

			wireless sensor network coverage area compared to the genetic algorithm.
St 17	Three Pheromones ACO, TPACO	Maximum Coverage, Energy Consumption	The new ACO algorithm (Triple Pheromone ACO, TPACO) uses three types of pheromones to efficiently find the solution, while traditional ACO algorithms only use one type of pheromone. Another advantage of the TPACO algorithm is that it uses fewer user parameters.
St 18	Adaptive Cauchy variational butterfly optimization algorithm (ACBOA)	Maximum Coverage	The BOA algorithm has been improved to enhance coverage rate by addressing issues such as falling into local optima and weak convergence performance. ACBOA has achieved a better coverage rate compared to BOA, ABC, FOA, and PSO.
St 19	Improved comprehensive learning particle swarm optimization (ICLPSO)	Maximum Coverage, Network Lifetime	Many experiments show that the proposed ICLPSO is effective and performs well under all these conditions, and QPSO also outperforms SPSO.
St 20	Dynamic Cuckoo Search Algorithm	Energy Consumption, Network Lifetime	Enhances network lifetime by using nodes with maximum residual energy, efficiently covers areas with fewer sensors, dynamically adjusts active and sleep modes for energy conservation. Complexity in real-world application due to dynamic energy levels and network conditions, may require more computational resources for continuous monitoring and adjustment.
St 21	Epsilon Constraint-based Adaptive Cuckoo Search	Congestion Avoidance and Control in Wireless Sensor Networks	High throughput (0,99), efficient in handling packet losses and delays, adaptively adjusts step size to find optimal solutions, reduces bandwidth consumption.Complexity of the algorithm might require more computational resources, specific to

			scenarios where congestion detection and control are critical.
St 22	Hybrid approach of Firefly Algorithm with Particle Swarm Optimization (HFAPSO)	Energy Consumption	In this paper, a hybrid approach combining Particle Swarm Optimization (PSO) with Firefly Algorithm (FA) is proposed to find the optimal cluster head selection in the LEACH-C algorithm. The hybrid algorithm enhances the global search behavior of fireflies using PSO and ensures the optimal positioning of cluster heads.
St 23	Energy Efficient Coverage based Artificial Bee Colony Optimization (EEC-ABC)	Maximum Coverage, Energy Consumption	The C-ABC algorithm, which provides both coverage and energy consumption optimization, addresses both problems as multi-objective compared to E-ABC. It optimizes both coverage rate and energy consumption better than ABC.
St 24	load balancing and routing strategies using the Glowworm swarm optimization approach (LBR-GSO)	Energy Consumption	LBR-GSO, along with metrics such as energy efficiency, energy consumption, and network lifetime extension. The results obtained from this comprehensive analysis indicate that LBR-GSO offers effective improvement compared to existing approaches such as ACO, EE-ACO, and s-Ant.
St 25	Survey Paper	Maximum Coverage, Energy Consumption	The study provides a comprehensive analysis by comparing the performance of various nature-inspired algorithms, offering valuable insights to guide readers in selecting the most suitable algorithms for specific applications. Additionally, it highlights the wide applicability of these algorithms by discussing their advantages and challenges across different application scenarios. However, as a survey paper, it lacks algorithm-specific details and does not delve deeply into the unique advantages or disadvantages of individual algorithms.

St 26	Survey Paper	Energy Consumption, Maximum Coverage	The study offers a comprehensive overview of swarm intelligence algorithms used in the Internet of Things (IoT), focusing on their applications in wireless sensor networks (WSNs). It emphasizes the potential of these algorithms to address challenges such as energy consumption, coverage optimization, and data routing in dynamic IoT environments. The paper also highlights the adaptability of swarm intelligence techniques to various IoT domains, showcasing their effectiveness in solving multi-objective optimization problems. However, as a survey paper, it provides limited implementation details and lacks experimental results, which may leave readers seeking more in-depth evaluations of specific algorithms.
St 27	Wolf Pack Optimization Algorithm	Maximum Coverage	Increases the neighborhood search range, improving the ergodicity and distribution uniformity of the wolf pack. Enhances calculation speed and accuracy of coverage optimization. Improves residual energy efficiency of sensor nodes significantly compared to Particle Swarm Optimization (PSO) and Artificial Fish Swarm Algorithm (AFSA).
St 28	elite parallel cuckoo search algorithm	Maximum Coverage	Compared to PSO and ACO-based methods, especially for WSNs with a large number of sensor nodes, it shows that it can increase regional coverage rate compared to traditional PSO and ACO approaches.
St 29	Elite Hybrid Metaheuristic Optimization Algorithm (EHMO)	Energy Consumption, Network Lifetime	Comprehensive simulation studies demonstrate that the proposed algorithm can increase the maximum lifetime of wireless sensor networks by 38% compared to results obtained with state-of-the-art algorithm routing algorithms based on other

			population-based optimization algorithms.
St 30	Improved Sparrow Search Algorithm, ISSA	Maximum Coverage	OA has been improved in terms of energy so that the algorithm can monitor the energy of each node, stop iterations when the node energy is low, reduce node energy loss, and decrease the number of dead nodes. This enhanced method optimizes the coverage area of the wireless sensor network.
St 31	Minimum exposure path (MEP-PSO)	Maximum Coverage	Directed sensors have been used, and by dynamically adjusting the locations of directed sensors, the coverage performance of DSNs can be significantly improved.
St 32	Improved whale algorithm	Maximum Coverage, Energy Consumption	In the model, the idea of inverse learning has been added to the original Whale Optimization Algorithm to optimize the initial distribution of the population. This method enhances the search capability of nodes and accelerates global search.
St 33	Grey wolf algorithm optimized by simulated annealing method (SA-GWO)	Maximum Coverage, Energy Consumption	GWO is more successful than PSO in optimizing both energy consumption and coverage rate.
St 34	Particle swarm and chaos combined method (PSO-VDCOA)	Maximum Coverage	Among the versions of PSO-VDCOA, PSO-Circle demonstrates better performance compared to PSO-Logistic, PSO-Gaussian, PSO-Chebyshev, PSO-Sinusoidal, PSO-Cubic, LdiwPSO, PSO, and CPSO algorithms, making it a viable choice for practical coverage optimization in WSNs.

St 35	A hybrid strategy-based improved weed algorithm (LRDE_IWO)	Maximum Coverage, Energy Consumpti on	The study presents an improved weed algorithm (IWA) tailored for coverage optimization in wireless sensor networks (WSNs). The algorithm effectively addresses challenges such as limited sensor coverage and high energy consumption by balancing global and local search capabilities. It prevents premature convergence and improves the optimization process through dynamic adjustments of parameters, ensuring higher coverage rates and reduced energy usage. However, the algorithm may require significant computational resources for fine-tuning parameters, which can be a limitation for large-scale WSN applications.
St 36	Cuckoo Search Algorithm	Maximum Coverage	Effectively jumps out of local optima using long-distance searches. Achieves global optimal solutions to maximize coverage performance. Can handle dynamic and complex environments due to the adaptable search pattern of Levy Flights. First to use cuckoo search for coverage hole repair in WSNs, introducing a novel approach.

The year in which the most publications were produced in the selected time period was 2020 (12 publications), and the year in which the least publications were produced was 2019 (2 publications). The number of publications produced in other years is as follows, as shown in Figure 2: 2016 is 3 publications, 2017 is 6 publications, 2018 is 3 publications, 2021 is 9 publications, 2022 is 5 publications and 2023 is 5 publications.

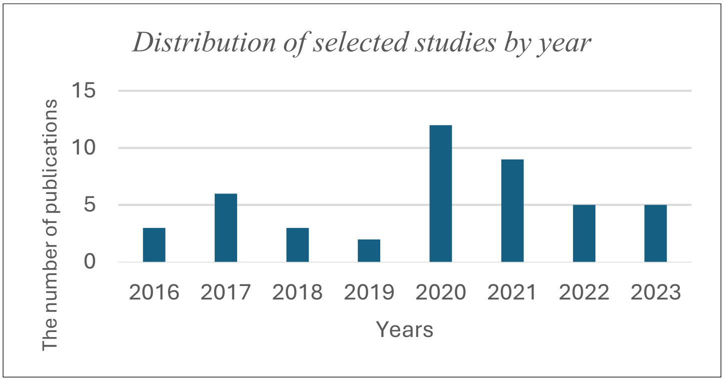

Figure 2. Distribution of Selected Studies by Year

When examining the distribution of selected studies by geographical locations, it is observed that the leading continent is Europe (n=21), followed by America (n=13), Asia (n=10), and Africa (n=1). The distribution of studies by countries where they were published is presented in Figure 3, and the distribution by geographical regions is shown in Figure 4.

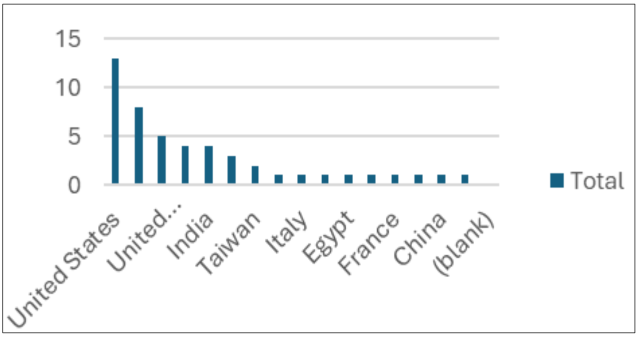

Figure 3. Geographical Distribution of Publications by Countries

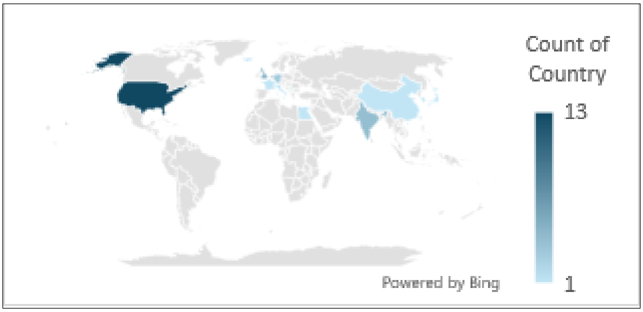

Figure 4. Geographical Distribution of Publications by Regions

4. DEFINITION OF TARGET COVERAGE PROBLEM

In the context of a wireless sensor network, the target coverage problem addresses the optimal placement of N sensors in a specific area. This problem aims to maximize the coverage ratio, where the coverage ratio represents the ratio of the area covered by the sensors to the region of interest. In Figure 5, $T = \{T_1, T_2, T_3, \ldots T_i\}$ represents the set of target points, and $S = \{S_1, S_2, S_3, \ldots . S_j\}$ represents the set of sensors. Additionally, it is assumed that all sensors are identical and each sensor can detect objects within its sensing range r.

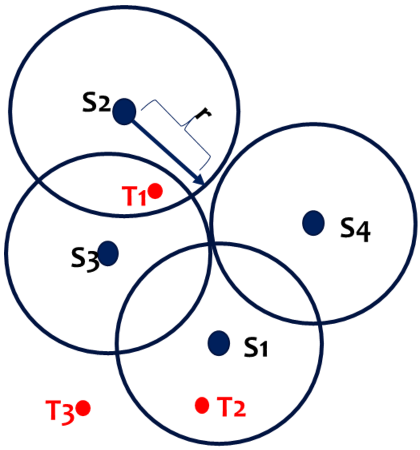

Figure 5. Target Coverage Problem

When the elements of target $T_i(x_i, y_i)$ and sensor $S_j(x_j, y_j)$ are deployed in the field, the coverage of target t_i by sensor s_j is calculated as shown in Equation 1.

$$d(Sj, Ti) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \leq r \quad (1)$$

Here, d is the Euclidean distance between the sensor and the target point. (x_j, y_j) and (x_i, y_i) are the coordinates of the sensor and target points, respectively. r is the sensing radius of the sensor node.

To measure coverage, Boolean disk coverage is commonly used (0: No coverage / 1: coverage exists). The coverage probability of sensor S_j for T is denoted by $p_{cov} = (S_j, T)$. A target is considered covered if it is detected by at least one sensor, as expressed in Equation 2.

$$p_{cov}(S_j, T) = \{ \begin{array}{l} 1\text{ , if } \mathrm{d}(\mathrm{S_j}, \mathrm{T}) < \mathrm{r} \\ 0, \text{ otherwise} \end{array} \quad (2)$$

Typically, the probability of a target being covered by a single sensor is less than 1. To increase the probability of coverage for a target, multiple sensors need to detect the target together. The joint coverage probability of all sensor nodes for a specific target is shown in Equation 3.

$$P_{cov}(S,T) = 1 - \prod_{s_j \in S} \left(1 - p_{cov}(S_j, T)\right) \tag{3}$$

Here, S represents all the wireless sensor nodes in the monitoring area. Area coverage ratio is one of the primary evaluation criteria of the coverage model. It is expressed as the ratio of the coverage area of the node set to the total area of the monitoring area, and the area coverage ratio of the node set is denoted as R_{cov} (S).

$$R_{cov}(S) = \frac{\sum P_{cov}(S,T)}{LW} \tag{4}$$

Here, $\sum \boldsymbol{P_{cov}}$ $(\boldsymbol{S},\boldsymbol{T})$ is the sum of the probabilities of target points being covered by all covering sensor nodes. Assuming the monitored area is a rectangle, the total area would be $\boldsymbol{LW}$ m^2.

When looking at the equations above, the problem to be solved falls into the category of NP-Hard.

NP-Hard problems belong to the NP (Non-deterministic Polynomial Time) class. There is no known polynomial-time algorithm that can solve all problems in the NP-hard problem class optimally. Examples include problems like the Traveling Salesman Problem (TSP) and the Knapsack Problem.

When the solution space is large, no polynomial-time method can be used to solve the problems described above. Various algorithms and methods can be used to solve NP-Hard problems, but these problems may not actually be solvable or their solutions may take a very long time. Therefore, for solving NP-Hard problems, acceptable solutions are generally sought, or the problems are transformed into easier problems by applying some constraints. Optimization algorithms are suitable solutions for such problems because they enable finding the desired result in polynomial time.

5. ALGORITHMS

Traditional optimization algorithms typically focus on fixed and specific problem types, while new generation optimization algorithms offer more flexible and dynamic solutions by drawing inspiration from natural systems and utilizing machine learning techniques. These new generation algorithms encompass evolutionary processes, swarm behaviors, artificial intelligence methods, and meta-heuristic approaches. For example, genetic algorithms, particle swarm optimization, ant colony optimization, among others, have become popular for solving complex problems. These algorithms can offer various advantages in problem-solving, such as optimizing multiple objectives, adapting to dynamic environments, and handling high-dimensional problems.

Therefore, the use of new generation optimization algorithms in solving the target coverage problem in mobile wireless sensor networks has the potential to provide more effective and efficient solutions. In this section, the advantages and disadvantages of some frequently used new generation optimization algorithms in the selected studies are discussed.

5.1. Particle Swarm Algorithm (PSO)

The Particle Swarm Optimization (PSO) algorithm is an optimization algorithm inspired by nature, which operates by mimicking the movements of bird flocks. The PSO algorithm can be applied to various optimization problems in wireless sensor networks, such as the target coverage optimization problem (Wang et al., 2020; Aziz et al., 2009). In this problem, the objective is to find the optimal distribution and timing of sensor nodes while minimizing energy consumption, extending network lifetime, and achieving maximum coverage of a specific target area.

The PSO algorithm can be used to find the optimal location for each sensor node that provides the best coverage area and to determine the optimal schedule for each sensor node that ensures the best connectivity and energy efficiency.

Following the definitions provided below, the PSO equation is given in Equation 5.

$$v_{ij+1} = v_{ij} + c_1 Rand_{1j}(t) * \left(pbest_{ij}(t) - x_{ij}(t)\right) + c_2 Rand_{2j}(t) * \left(gbest_j(t) - x_{ij}(t)\right) = x_{ij}(t) + v_{ij}(t+1). \tag{5}$$

Where:
(1) i.particle $X_i = (x_{i1}, x_{i2}, \ldots, x_{in})$.
(2) The current speed of particle i is $V_i = (v_{i1}, v_{i2}, \ldots, v_{in})$.
(3) Personal best position of particle i is $pbest_i = (pbest_{i1}, pbest_{i2}, \ldots, pbest_{in})$.
(4) the best position of the group being gbest

In Equation 5, the index "j" represents the dimension of the problem being searched by the particles; "i" represents the number of particles; "t" denotes the iterations; c_1 and c_2 represent the acceleration coefficients in the algorithm and typically range from 0 to 2; " $Rand_1$" and " $Rand_2$" are two independent uniformly distributed random variables, ranging from 0 to 1.

In the context of the PSO algorithm, gbest_j represents the best global position among all particles for the dimension j. Here, j refers to the dimensionality of the problem being optimized, and gbest_j indicates the coordinate value of the globally optimal solution in the j-th dimension at the current iteration. This value is determined by comparing the personal best positions (pbest) of all particles in the swarm. The gbest_j value is then used to guide the particles in the swarm towards this optimal solution in subsequent iterations.

The output of the PSO algorithm is the optimal position of each sensor node that ensures the best coverage of the target area.

Some advantages and disadvantages of PSO algorithms in WSN coverage area optimization are as follows:

Advantages:

- PSO is a simple, effective, and computationally efficient optimization algorithm that can find solutions close to the optimum for complex and nonlinear problems.
- Implementation of PSO is easy, and it requires only a small number of parameters to be adjusted, making it suitable for WSN applications.
- PSO can adapt to dynamic environments and handle multiple objectives simultaneously, which are important features for WSN coverage area optimization.

Disadvantages:

- PSO may suffer from early convergence and stagnation, meaning that particles can get trapped in local optima and cease to explore the search space.
- PSO may struggle to address constraints common in WSN coverage area optimization problems. Constraints can limit the feasibility and diversity of solutions, affecting the convergence speed and quality of the algorithm.
- PSO may require a large number of iterations and evaluations to reach a satisfactory solution, leading to more time and energy consumption in WSN applications.

5.2. Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a popular optimization algorithm used in various fields, including WSN. ACO is an optimization algorithm developed by taking inspiration from the foraging behavior of ants in nature (Dorigo & Stützle, 2004).

This algorithm utilizes a group of artificial ants to solve a problem. Each ant represents a solution path, and the ant colony attempts to solve the problem by exploring these paths while sharing information. ACO employs a probability-based search method to find the best solution. The ant colony can be effectively utilized to optimize a problem or find the best route, and it is often applied to complex and large-scale data problems. In the context of WSN, ACO can be applied to address many important challenges such as routing, coverage, energy efficiency, and data fusion.
Advantages and disadvantages of the ACO algorithm in WSN coverage area optimization are as follows:

Advantages:

- It is an algorithm capable of conducting simultaneous searches over a large population.
- It allows minimizing the computational burden of finding the optimal or near-optimal path or paths.

Disadvantages:

- In some cases, it can provide slow convergence, meaning it may require long durations to reach the desired outcome. This could pose issues in real-time applications.
- The effectiveness of ACO depends on accurately tuning a set of parameters. Selecting and tuning these parameters can be challenging in some cases.
- ACO is a probability-based search algorithm and therefore does not always guarantee the global optimum. There may be a chance of finding a better solution in some cases, but there is no guarantee of providing exact results.

In conclusion, ACO is a powerful optimization tool that can be used for WSNs, but it should be applied carefully and configured according to the problem requirements. Its advantages generally outweigh its disadvantages, but it requires proper parameter settings and design decisions.

5.3. Whale Swarm Algorithm (WGA)

The Whale Optimization Algorithm is the launch of a metaheuristic plugin that mimics the hunting behavior of humpback whales. This update can be used to resolve various issues such as WSNs.

The schedule and results of this new method are listed below:

Advantages:

- The Whale Optimization Algorithm offers the ability to more effectively approximate local and global optima. This increases the ability to obtain better results for a variety of problems (Gu, 2020).
- Whale Optimization Algorithm is capable of handling multiple expansion problems with different parts. This presents speech in a more attractive way in various application areas (Gu, 2020).
- Note that this attenuation requires less parameter speedup than some other security techniques.

Disadvantages:

- The convergence speed of the algorithm can sometimes be slow, especially for large and complex problems. This may be a disadvantage in applications of time differences (Deng et al., 2023).
- The Whale Optimization Algorithm may produce results with low precision in some problems. This may limit use in high-definition applications (Deng et al., 2023).
- It is possible for the algorithm to lose local optima, but for some problems it can be made more difficult with better results.

5.4. Grey Wolf Algorithm (GWA)

The coverage problem in WSN addresses the optimization of sensors' ability to effectively cover a certain area. The Grey Wolf Algorithm offers a nature-inspired population-based optimization approach to tackle this challenge. The algorithm mimics the behaviors of grey wolves and updates the positions of sensors like these wolves. Through collaboration among leaders, followers, and other roles, sensors optimize their positions and aim to increase coverage. It utilizes crossover and mutation operations reminiscent of genetic algorithms to determine the best positions during iterations. As a result, the Grey Wolf Algorithm is considered a powerful tool for solving coverage problems in WSNs and determining the optimal positions of sensors.

The advantages and disadvantages of the Grey Wolf Algorithm for the coverage problem in WSNs are as follows:

Advantages:

- The Grey Wolf Algorithm adopts a population-based approach and allows for the simultaneous evaluation of many different positions, providing an advantage in exploring alternative solutions.
- The algorithm includes crossover and mutation operations used in genetic algorithms, thus maintaining genetic diversity and the ability to discover new positions.
- Grey wolves update the positions of sensors using leadership, followership, and other roles, enabling them to adapt to environmental changes.

Disadvantages:

- The success of the algorithm depends on specific parameter settings, making it challenging to adjust these parameters correctly.
- The Grey Wolf Algorithm may sometimes exhibit slow convergence, requiring more iterations to achieve the desired outcome.
- The cost of sensor displacement and the requirement for continuous movement can be disadvantages in practical applications.
- The Grey Wolf Algorithm does not always guarantee the global optimum, meaning there is a chance of finding the best solution, but no guarantee of precise results.

In conclusion, the Grey Wolf Algorithm can be an effective optimization tool for addressing coverage problems in WSNs, but careful attention to parameter settings and problem requirements may be necessary. Its advantages generally outweigh the disadvantages, but this may vary depending on the problem context and application scenario.

5.5. Cuckoo Search Algorithm (CSA)

CSA is an optimization algorithm inspired by nature. This algorithm is based on the breeding and nest robbing behavior of cuckoos.

Each cuckoo represents a potential solution and expresses this solution with a nest. The purpose of the Cuckoo Algorithm is to find the smallest or largest value of an objective function (Tian et al., 2021).

CSA has 3 main parameters.

- Population Size: Specifies how many cuckoos will be used for the algorithm (Tian et al., 2021).
- Breeding Rate: It is a rate that controls how many offspring the cuckoos will leave from the current nest when breeding. This rate determines the frequency of new solutions joining the population.
- Egg Laying: Cuckoos lay eggs in nests (Tian et al., 2021). How to place eggs in nests is important when coming up with new solutions.

How the Algorithm Works:

- Cuckoos produce new solutions using existing nests (solutions). The new solutions produced are placed in some of the existing slots. This fitting process evaluates whether the new solution improves the existing slot. Better solutions favor existing slots and bad solutions are eliminated over time (Narawade & Kolekar, 2017).
- The algorithm continues to run until it reaches a certain stopping criterion or exceeds a certain number of iterations (Narawade & Kolekar, 2017).

Advantages:

- Can Solve High Dimensional and Complex Problems: CSA can deal with high dimensional, complex and nonlinear optimization problems. This provides a great advantage in solving the coverage problem in WSNs (Narawade & Kolekar, 2017).
- Avoidance and Convergence Ability: CSA has the ability to avoid local optima and converge to global optima. This makes it easier to obtain better solutions (Masoodi et al., 2018).
- Suitability for Dynamic Environments: CSA stands out for its ability to adapt to challenging conditions such as changing network topologies and dynamic environments. This is important to adapt to the changing conditions of WSNs (Zhuang et al., 2017).

In (Thirugnanasambandam et al., 2021) authors proposed novel Multi-Objective Binary Reinforced Cuckoo Search Algorithm (MOBRCSA) designed for solving connected coverage target-based problems in WSNs, particularly addressing critical targets. MOBRCSA efficiently balances multiple objectives such as minimizing the number of deployed nodes, maximizing coverage, and ensuring connectivity.

Disadvantages:

- CSA may require a large number of iterations and evaluations. This can be costly in terms of time and computational resources (Alia & Al-Ajouri, 2017).
- Parameter Tuning Challenges: CSA may require parameters to be tuned correctly. Incorrect parameter settings may negatively affect the performance of the algorithm (Narawade & Kolekar, 2017).

6. CONCLUSION

In this study, a survey was conducted to explore optimization algorithms aimed at maximizing coverage within Wireless Sensor Network (WSN) areas of interest. The review included 45 articles, underscoring the crucial importance of coverage optimization, a topic of growing interest among researchers. Recently, nature-inspired algorithms have emerged as effective solutions for addressing challenges related to maximizing target coverage and enhancing energy efficiency within WSNs.

As mentioned in Table 1, among the various algorithms reviewed, the Cuckoo Search (CS) and Grey Wolf Optimization (GWO) algorithms were identified as particularly effective. These algorithms are favored in the literature due to their robust ability to avoid local minimal and efficiently converge on global optima, which significantly reduces computational complexity compared to other methods. The CS algorithm, for example, excels in achieving higher coverage rates by adapting its search strategy dynamically, which is crucial for extensive and unpredictable WSN environments. Similarly, the GWO algorithm has shown superior performance in optimizing both energy consumption and coverage rate, thanks to its simulated annealing-enhanced search capabilities.

This review highlights the pivotal role that advanced optimization algorithms play in enhancing the functionality and sustainability of WSNs. The ongoing development of such algorithms is vital for advancing network technologies and catering to the increasing demand for smart and efficient monitoring systems in various applications.

Authors' Contribution
In this study, the first author contributed to the research, data collection, analysis, interpretation, literature review, and writing of the article. The second author contributed to the idea, criticism, and writing of the article. The third author contributed to the idea, criticism, and writing of the article.

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There is no conflict of interest between the authors.

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Research and publication ethics were followed in the study.

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